Race Identification for Face Images

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***Abstract*—Humans are able to process a face in a variety of ways to categorize it by its identity, along with a number of other demographic characteristics, including race, gender , and age. Experimental results are based on a face database containing subjects. Race and gender also play an important role in face-related applications. Experimental results are indicated that participants categorized the race of the face and this categorization drives the perceptual process. A face image data set is collected from Internet, and divided into a training dataset and a test dataset. Experimental results based on a face database containing 250 subjects. The proposed system can also be applied to other image-based classification tasks.**

***Index Terms*— race identification, PCA, face recognition**

I. Introduction

Race refers to classifications of humans into relatively large and distinct populations or groups often based on factors such as appearance based on heritable phenotypical characteristics or geographic ancestry, but also often influenced by and correlated with traits such as culture, race and socio-economic status. As a biological term, race denotes genetically divergent human populations that can be marked by common phenotypic traits. Humans are able to process a face in a variety of ways to categorize it by its identity, along with a number of other demographic characteristics, including race, gender, and age. Over the past few decades, a lot of effort has been devoted in the biological, psychological, and cognitive sciences areas, to discover how the human brain perceives, represents and remembers faces. Computational models have also been developed to gain some insight into this problem. The demographic features, such as race and gender, are involved in human face identity recognition. Humans are better at recognizing faces of their own race than faces of other races [3] [4]. Golby et al. Show that same-race faces elicit more activity in brain regions linked to face recognition [5]. They use functional magnetic resonance imaging (fMRI) to examine if the same-race advantage for face identification involves the fusiform face area (FFA), which is known to be important for face recognition [6]. Compared to race identification, the gender classification has received more attention [7] [8] [9]. Gutta et al [9] proposed a hybrid classifier based on RBF networks and inductive decision trees for classification of gender and race origin, using a 64*72 image resolution. They achieved an average accuracy rate of 92% for the ethnic classification part of the task. Experimental results for gender classification in Moghaddam and Yang [7] are based on 21*12 image resolution. Shakhnarovich et al [10] presented a real-time face detection and recognition system based on a boosted classifier. The same structure is used for demographic information extraction, including gender and race. Two categories of race are defined, Asian and non-Asian. Again, their system is focused on low resolution (24824) images with face data weakly aligned. Their reported accuracy is about 80%. The other-race effect for face recognition has been established in numerous human memory studies and in meta-analyses of these studies [11],[12],[13]. In fact, the other-race effect in humans can be measured in infants as a decrease in their ability to detect differences in individual other-race faces as early as three to nine months of age [13].

II. Pre-processing

The first step of pre-processing is the face region extraction. Face region extraction means the input face image is extracted from input image by using cropping tool. The input color image is converted to gray image and stored in database for processing. The input image may be current scanned image or realities input image. And then enhancing state occurs. The proposed system allows the free size and format of color image. Enhancing state is included the noise filtering, gray scale converting, and histogram equalization. Histogram equalization is mapped the input image's intensity values so that the histogram of the resulting image will have an approximately uniform distribution. The histogram of a digital image with gray levels in the range [0, *L*-1] is a discrete function.

$$p(rk) = \frac{nk}{n} \qquad (1)$$

where L is the total number of gray levels , r_k is the k^{th} gray level, n_k is the number of pixels in the image with that gray level, n is the total number of pixels in the image, and $k = 0, 1, 2, \ldots, L - 1$. $p(r_k)$ is given an estimate of the probability of occurrence of gray level r_k. By histogram equalization, the local contrast of the object in the image is increased, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensity can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast without affecting the global contrast.

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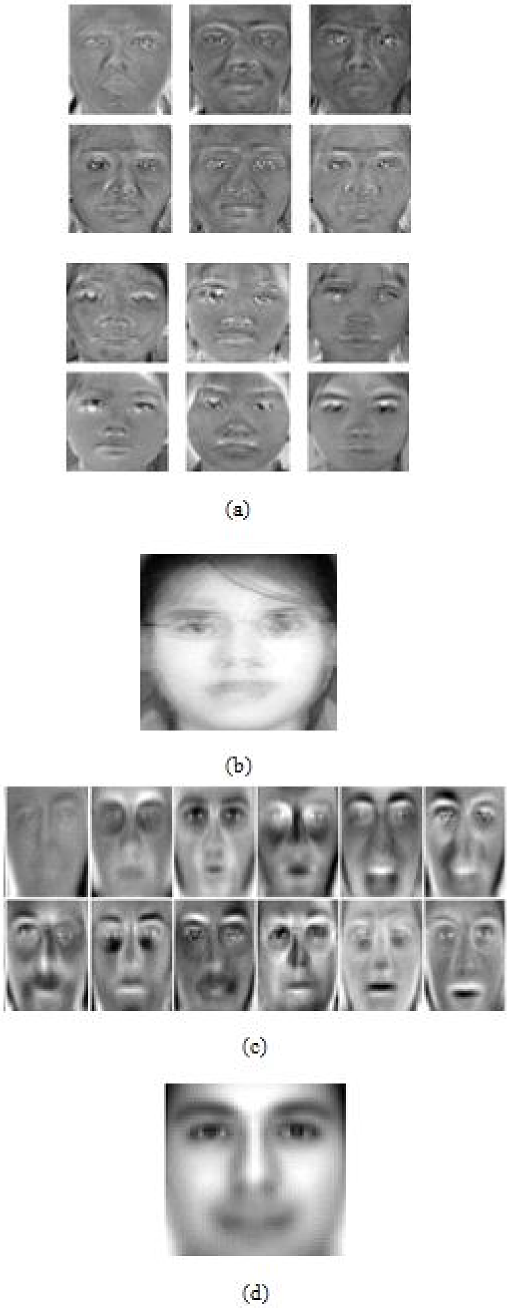

Figure 1. PCA on Myanmar and Non-Myanmar datasets. (a) “average” Myanmar face; (b) top 12 eigenfaces of Myanmar dataset;(c) “average” Non-Myanmar face; (d) top 12 eigenfaces of Non-Myanmar dataset.

III. Feature Extraction

A. Subspace Face Recognition

The Principal Component Analysis (PCA) can do prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, applications having linear models are suitable. Let us consider the PCA procedure in a training set of M face images. Let a face image be represented as a two dimensional N by N array of intensity values, or a vector of dimension N^2. Then PCA tends to find a M-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lower dimensional ($M << M << N2$). New basis vectors are defined a subspace of face images called face space. All images of known faces are projected onto the face space to find sets of weights that described the contribution of each vector. By comparing a set of weights for the unknown face to sets of weights of known faces, the face can be identified. PCA basis vectors are defined as eigenvectors of the scatter matrix S defined as:

$$S = \sum_{i=1}^{M} (xi - \mu).(xi - \mu)' \qquad (2)$$

where μ is the mean of all images in the training set and x_i is the i^{th} face image represented as a vector i. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. A facial image can be projected onto $M'(<< M)$ dimensions by computing

$$\Omega = [v_1 v_2 \ldots v_{M'}]^T \qquad (3)$$

The vectors are also images, so called, eigenimages, or eigenfaces.They can be viewed as images and indeed look like faces. Face space forms a cluster in image space and PCA gives suitable representation.

B. Nearest Neighbor Classification

One of the most popular non-parametric techniques is the Nearest Neighbor classification (NNC). NNC asymptotic or infinite sample size error is less than twice of the Bayes error [15]. NNC gives a trade-off between the distributions of the training data with a priori probability of the classes involved [14]. KNN (K^{th} nearest neighbor classifier) classifier is easy to compute and very efficient. KNN is very compatible and obtain less memory storage. So it has good discriminative power. Also, KNN is very robust to image distortions (e.g. rotation, illumination). Euclidian distance is determined whether the input face is near a known face. The problem of automatic face recognition is a composite task that involves detection and location of faces in a cluttered background, normalization, recognition and verification.

IV. Conclusions

This paper has addressed the race identification problem based on facial images. The Principal Component Analysis (PCA) based scheme has been developed for the two-class (Myanmar vs. non-Myanmar) race classification task. An ensemble framework, which integrates the PCA for the input face images at multiple scales, is proposed to further improve the classification performance of the race identification system. Experimental results based on a face database containing 250 subjects are encouraging. The normalized classification scores can be used as the confidence with which each image belongs to a race class. This confidence is helpful to the image-based face recognition, and cross-race face recognition. Separating the race factor from the other

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factors can help the recognition system to extract more identity-sensitive features, thereby enhancing the performance of the current face identity recognition systems. The proposed system can also be applied to other image-based classification tasks. Future experiments using racially ambiguous faces need to involve participants of other races.

V. Experimental Results

A face image data set is collected from Internet, and divided into a training dataset and a test dataset. Using face detector and face alignment tool, these faces are automatically cropped and normalized in grey level and geometry as in [6], and each face is manually labeled with an age value estimated by human subjectively. The dataset is separated into two race groups, Myanmar and Non-Myanmar. The Non-Myanmar database is composed of research papers. Most of the Myanmar faces are of Kachin, Kayah, etc. origins. These face images are contained variations in pose, illumination and expression. Sample images from the databases are shown in Fig. 3.

(a)

(b)

Figure 3. Representative faces in the database . (a) Myanmar; (b) Non-Myanmar.

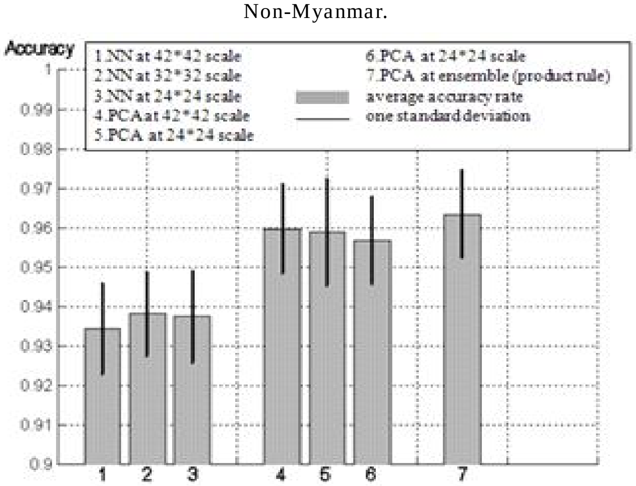

Figure 4. Performance comparison

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